Evidence of the Contribution of Legal Insider Trading to Market Efficiency

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Abstract

Does legal insider trading contribute to market efficiency? Using the refinement proposed by the recent microstructure literature, we analyze the information content of legal insider trading. Our sample encompasses 2,110 different companies subject to 59,244 aggregated daily insider trades over the period from January 1995 to the end of September 1999. Our main findings are the followings. (i) Consistent with previous literature, financial markets offer a mild response in terms of abnormal returns to insider trading activities. (ii) The univariate analysis of stock prices on insider net purchase and net sale days suggests insiders' market timing ability. (iii) Market liquidity seems to be weaker on insider net purchase days, indicating that net buyer insiders are on average market liquidity consumers. (iv) Market liquidity seems to be higher on insider net sale days, indicating that net seller insiders are on average market liquidity providers. (v) The analysis of the considered information proxy reveals that insiders enhance market efficiency. Insider trading clearly permits faster price discovery on insider trading days. (*JEL* G14; G18)

Keywords: legal insider trading, market efficiency, order imbalance.

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"Our markets are a success precisely because Americans enjoy the world's highest level of confidence. [...] Investors trust that the marketplace is honest. They know that our securities laws require free, fair and open transactions."

Arthur Levitt, Chairman of the SEC
Address before the "SEC speaks" Conference, February 1998

Does legal insider trading contributes to market efficiency? In this paper, using the refinement proposed by the recent microstructure literature, we propose to analyze the information content of <u>legal</u> insider trading. This is an important question since insider trading regulation plays an important role in economies with developed stock markets. According to Battacharchya and Daouk (2002), the existence of insider trading laws and their enforcement is essentially a phenomenon of the 1990s. One interesting aspect of these regulations is that they allow insiders to trade their own companies' stocks under certain conditions. For example, under US securities laws, legal insider trading occurs every day when corporate insiders – officers, directors or employees – buy or sell stock in their own companies.[1]

The social utility of regulating insiders' trading has been deeply debated in the literature. Indeed, there are several important contributions which analyze the impact of insider trading and its regulation on economic efficiency. On the one hand, critique of insider trading regulation argues that restrictions are inefficient because insider trading allows new private information to be priced more quickly. Stock prices, therefore, reflect intrinsic firm value more accurately, promoting improved economic decision-making and resource allocation (e.g., Manne, 1966; Carlton and Fischel, 1983; Glosten, 1989; Manove, 1989; Leland, 1992). Moreover, Tighe and Michener (1994) argue that merely private interests are served by insider trading laws (e.g.,

[1] One of the constraints is that the insiders have to report their trading to the Securities and Exchange Commission (SEC). Once the trading is completed, files have to be sent to the SEC, which publishes them.

brokers, arbitrageurs and portfolio managers), as small investors lack the political organization to lobby for such laws. On the other hand, those in favor of insider trading regulation essentially claim that regulation promotes public confidence and participation in the stock market and allows outsiders to share in value-enhancing events on an equal footing (Ausubel, 1990).

One clear message which arises from this intensive debate is that authorizing insiders to trade should be based on a balance between allowing private information to be priced (enhancing market efficiency) and preserving market integrity (avoiding unfair enrichment by those with access to privileged information). As pointed out by Huddart *et al.* (2001), the regulatory objectives of public disclosure of insider trading are to reduce the information asymmetry between insiders and outsiders. However, there is always a delay between the realization of insider trading and public announcement of this.[2] Therefore, to fully justify regulated insider trading, we need, in return, a contribution to market efficiency.

Consequently, the research question we are interested in is the following: do legal insider trading activities contribute to market efficiency? In other words, does information affect prices more quickly thanks to legal insider trading activities? This is an essential question because previous studies, using mainly portfolio approaches, document that insiders outperform the market over a time horizon ranging from one month to several months (e.g., Jaffe, 1974; Finnerty, 1976; Seyhun, 1986 and 1998;

[2] In the United States, according to Section 16(a) of the Securities and Exchange Act of 1934, insiders are required to report their transactions by the tenth day of the calendar month after the trading month. In our sample, the average reported period is around 22 days. It is important to note that since August 2002, according to the Section 403(a) of the Sarbanes-Oxley Act of 2002, insiders are required to report their transactions before the end of the second business day following the day on which the subject transaction has been executed.

Lin and Howe, 1990; Jeng *et al.*, 2003).[3] Are these abnormal gains really evidence of private information revelation by the action of better-informed agents? We see at least another two competing explanations. First, these abnormal gains could be the manifestation of some latent risk factors such as size, earnings/price or book-to-market (e.g., Rozeff and Zaman, 1988; Lakonishok and Lee, 2001). The second possible explanation is that these abnormal returns, since they are computed over an event window of several months, could reflect the price reaction to subsequent public announcement (within the event window) of previously private information. Therefore, it is still questionable whether insiders contribute to faster price discovery. Moreover, these portfolio approaches are subject to significant bad-model problems, which are even more serious for long-term returns analysis (see comments of Fama (1998) about long-term event studies).

The relevance of our research question stems also from the fact that (informed) insider trading profit is realized at the expense of outside investors, even if total welfare may increase or decrease depending on the economic environment (Leland, 1992). Moreover, we do not have a clear-cut answer from the literature as to whether outsiders can profit by using the publicly available information concerning insider trading once they are reported to the SEC (e.g., Seyhun, 1986; Rozeff and Zaman, 1988).[4] Therefore, the necessary condition that needs to be satisfied in order to justify allowing insiders to trade on their private information is that their trading should enhance market efficiency. This is what we propose to test in this paper.

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[3] However, there is a notable exception to this general finding, which is the study by Eckbo and Smith (1998). They report that insiders in firms on the Oslo Stock Exchange do not earn abnormal profits.

[4] However, Seyhun (1992) provides evidence that insider trading has some predictive ability of future stock returns. In the same way, Bettis *et al.* (1997) show that outside investors can earn abnormal profits by analyzing publicly available information about large insider trades by top executives. Lakonishok and Lee (2001) report also that insiders seem to be able to predict cross-sectional stock returns. Their result, however, is driven by insiders' ability to predict returns in smaller firms.

To address this question, we use an extensive U.S. database of legal trading realized by insiders covering the period from January 1995 to the end of September 1999. Our sample includes 59,244 aggregated insider open market episodes. Previous studies mostly look at what is happening ex post to insider trading in terms of abnormal gains for insiders and/or outsiders (portfolio performance), while we are more interested in what is happening on insider trading days in terms of price discovery. Our focus on the short-term impact of insiders' trading activities to capture information effects is motivated by recent evidence presented by Chordia *et al.* (2005). These authors show that it takes only five minutes for astute investors to begin efficiency-creating actions.

It is also important to note that there are some studies that appraise the impact of insider trading activities over a shorter period. Seyhun (1986), and more recently Lakonishok and Lee (2001) provide short-term event study results on US legal insider trading. They observe statistically significant, but economically unimportant market movements around insider net purchases and net sales.[5] Using the same event study method, we confirm this result with our sample of insider trades. Recently, within the UK context, Fidrmuc *et al.* (2006) report abnormal returns which is three times as high as the one provided by Lakonishok and Lee (2001).[6] Jenter (2005) interprets the lack of evidence for economically significant insider abnormal returns as that the corporate insiders in US may not use much valid inside information.[7]

[5] Note that the statistical significance of this result is subject to active debate in the literature (see e.g. Buttler *et al.*, 2005; Baker *et al.*, 2006).

[6] One possible explanation provided by the authors is the speedier reporting of trades in the UK compared to the US.

[7] However, it is important to note that the small returns associated with insider trades could be considered as economically significant given these trades combine transactions that are uninformative and others that do contain information.

But aside from the debate about the economic significance of the abnormal return around insider trading days, its use to infer insiders' information-motivated trading seems to be subject at least to two shortcomings. The first one is related to the likely endogenous relation between the abnormal returns and insider trading. The insiders can decide to purchase on a specific day because they expect that stock prices will increase on that day. The second shortcoming is related to the fact that the abnormal returns could be a noisy proxy for private information, essentially because insiders can act also strategically by timing the market, and choosing voluntarily a trading window in which they can hide their trading motivation (see, Jenter, 2005, and Piotroski and Roulstone, 2005). For example, the insider may submit a buying trade when the price is declining. Hence, the resulting abnormal return would be an underestimation (overestimation) for the purchases (sales) of the true abnormal return. In such a context, the abnormal return for a given insider trading day could be the sum of at least two effects: (1) the price impact of the private information, and (2) the market timing of the insider.

To sum up, on the one hand, if we consider that the abnormal returns generated on insider trading days are economically important, we are not sure about the direction of the causation. On the other hand, if we think that the abnormal returns are too small to be economically significant, we are left with a puzzling result. These two phenomena are likely to be present and to compensate each other on a large sample of insider trades.

Our contribution to the literature lies in the fact that our study is built on an improved measure of information incorporation, grounded in recent market microstructure literature and permitting the study of insider purchase and sale activities on a large sample of (even low liquid) firms (and insiders' transactions). Our approach is close to the one of Chordia *et al.* (2005) in the sense that we measure the "contribution to market efficiency" by using the contemporaneous relationship between the return and the relative order imbalance. Moreover, focusing on the trading mechanism (the price impact of the relative order imbalance) allows us to analyze insider purchases as well sales and to overcome the two shortcomings affecting the abnormal return approach identified here above. The abnormal price sensitivity to relative order imbalance due to insider trades is without ambiguity a consequence of their trading behavior.

Our main findings can be summarized as follows. We compute the abnormal returns associated to insider net purchases and net sales in order to replicate the Lakonishok and Lee (2001) results. This is just to ensure that we are in the same empirical context. Our univariate analysis highlights insiders' market timing ability. Stock prices on insider net purchase (sale) days tend to be smaller (greater) than the ones on the other days. Market liquidity seems to be weaker on insider net purchase days, suggesting that insiders are on average market liquidity consumers. But in return, they enhance market efficiency, because insider abnormal purchases are associated with faster price discovery. That is, the association between the relative order imbalance and market return is larger on days on which insiders are net purchasers. With respect to insider sales, market liquidity seems to be greater on insider net sale days, suggesting that insiders on average are market liquidity providers. Moreover, the sensitivity of the return on the relative order imbalance is higher in absolute value, which indicates that insider abnormal selling activities also clearly permit faster price discovery.

This paper is closely related to the work of Damodaran and Liu (1993) where the authors identify an experimental context where it is possible to isolate the presence of private information and to value its economic content. Focusing on a very small sample of insider trades[8], they provide evidence of private information revelation through the trading of corporate insiders of real estate investment trusts following their company assets' appraisals. Insiders seem to believe on this reevaluation, and trade on it to make profit, and in the process reveal their information to the market. The later public disclosure of the reevaluation is not associated with significant market reaction. It is important to note that, in addition to the small sample size of their study, the authors do not provide a clear distinction between the insider trades analyzed and the concept of illegal insider trading.[9] Our work can be seen as a generalization of the finding of Damodaran and Liu (1993) on a large sample of insider trades, while focusing on legal insider trading without having any knowledge of the existence of private information.

There are also other papers that provide indirect evidence that the stock market responds quickly to insider trades. For example, Jeng (1999) and Bettis *et al.* (2000) analyze the trading rates and information asymmetry measure on blackout period (a period on which companies restrict trading in their stock by their own insiders). They document that trading rates are much higher during allowed trading days and that the adverse-selection component of the spread is higher as well during those days on which the probability of insider trades is relatively high.

[8] Their sample encompasses only 35 transactions (23 purchases and 12 sales) in a 6-month period before the appraisal, and 45 transactions (40 purchases and 5 sales) between the appraisal month and its public disclosure.
[9] With respect to illegal insider trading, there are several contributions in the literature that show the incorporation of information into asset prices around days of the illegal trades (see, a.o, Battacharya *et al.*, 2000).

The paper is organized as follows. Section 1 describes the methodology adopted to measure the contribution of legal insider trading to market efficiency. Section 2 describes the data. Section 3 presents our analysis of how legal insider trading activities contribute to market efficiency. Section 4 concludes.

1. Measuring "the Contribution to Market Efficiency"

The recent microstructure literature proposes three main approaches for measuring information-based trading. The first one is based on spread and on its adverse selection component. This method is subject to serious criticism in the literature, mainly related to the fact that competing spread decomposition models seem to provide different results (Van Ness *et al.*, 2001; Neal and Wheatley, 1998).

Another widely used approach to measure information-based trading is the permanent price impact measure originated by Hasbrouck (1991a; 1991b). Here the theory is that the more informative trading is, the bigger its permanent price impact should be. By the use of a vector autoregressive model, Hasbrouck models the dynamic between the price changes and the order flow (through the trading). By assuming that it is the unexpected part of the order flow which incorporates private information, Hasbrouck computes the permanent (long-term) price impact of such trading and uses it as an indicator of information based-trading. While this method is clearly attractive, its major empirical shortcoming is the need for a large amount of observations. Vector autoregressive models require a large amount of high-frequency data to be estimated, which limits in practice the applicability of the method to actively traded stocks. This weakness is not, in our case, without consequences. We may indeed expect that insider trading activities impact more strongly on the speed of the price discovery process for low liquid stocks.

The last important microstructure-based information asymmetry measure is the probability of information-based (PIN) trading introduced by Easley *et al.* (1996). This measure is based on a structural sequential trade model, and has led to numerous applications in empirical finance. Its widespread use most likely originates from the structural model on which it is based as well as from its appealing empirical tractability. Only classified trades (buyer or seller initiated) are needed. However, its information content is not clear enough. This model simply argues that the likely reason for a discrepancy (if any) between buyer and seller initiated trading is the trading activity of informed traders. Aktas *et al*. (forthcoming *Journal of Financial Markets*) underline the limits of such a conjecture, analyzing the PIN behavior around M&A announcements.

To analyze whether insider trades are information-motivated, we develop an alternative approach, designed to tackle the limitation of the above-mentioned approaches. Aktas *et al.* (forthcoming *Journal of Financial Markets*) have shown that PIN is simply trade imbalance statistics. Indeed, PIN corresponds to the ratio between the expected absolute order imbalance (absolute difference between buys and sells, namely OIB) and the expected volume. The daily PIN can be proxied empirically by the daily relative order imbalance, the ratio between the daily imbalance and the daily volume. Starting from this observation, our approach is based on ideas developed in Hasbrouck (1991a; 1991b), Chordia *et al.* (2005), and Aktas *et al*. (forthcoming *Journal of Financial Markets*). We measure the “contribution to market efficiency” by estimating the contemporaneous correlation between daily return and daily relative OIB. Only the component of the relative order imbalance that has an impact on the return is expected to convey valuable information. Its uncorrelated part is most likely driven by liquidity motivated trading. This is because we know that order imbalances arise either from traders who believe themselves to be in the possession of pertinent information, or from traders who experience large liquidity shocks (Chordia *et al.*, 2002). In order to disentangle these two components, we study within a panel regression framework the correlation between the daily return and our private information measure.

More specifically, for each one of our sample securities and for each trading day, using intraday quote and transaction data, we measure the signed relative OIB (*ROIB*) for day *t* and stock *i* as follow:

$$ROIB_{i,t} = \left(B_{i,t} - S_{i,t}\right) / \left(B_{i,t} + S_{i,t}\right), \qquad (1)$$

where $B_{i,t}$ and $S_{i,t}$ correspond to the number of buys and sells for day *t* and stock *i*, respectively. We also use two alternative specifications for the *ROIB*: the *volume ROIB*, where *B* and *S* are expressed in the number of shares exchanged, and the *value ROIB*, where *B* and *S* are the buy and sell volumes in monetary value. The first measure of *ROIB* ignores the size of the trade, counting small orders in the same way as large orders. The *volume* and *value ROIB* weights large orders more heavily.

Since only the component of the *ROIB* that generates a price impact is expected to signal private information, in a second step we analyze within a panel regression framework the sensitivity of the daily return to the daily *ROIB* computed using intraday transaction data. This is given by the following equation:

$$R_{i,t} = \alpha_i + \beta \, ROIB_{i,t} + \varepsilon_{i,t} \,. \qquad (2)$$

The coefficient β measures the normal level of the price sensitivity to the *ROIB*. Our aim is to measure the impact of insider trades on this coefficient, which would correspond to the abnormal change in sensitivity due to insider trading. The intuition underlying our test is summarized in Figure 1. The coefficients δ_{BUY} and δ_{SELL} capture the abnormal change in the sensitivity induced by insider buy and sell transactions, respectively. If insider trades are information-motivated, insider purchases should increase the price sensitivity to a positive order imbalance (Panel A), and decrease the price sensitivity to a negative order imbalance (Panel B). In this latter case, information-motivated insider purchases would attenuate the sell order imbalances of others. Indeed, if *ROIB* is positive, then its coefficient should be larger on days when insiders purchase too, but when *ROIB* is negative, the price sensitivity to order imbalance on insider purchase days should be smaller in absolute value than the price sensitivity on the other days. The reasoning is the same for insider sells.

To capture the asymmetric relationship between the return and the interaction of the *ROIB* and insider trades, we consider the *ROIB* in absolute value, and estimate the following general equation within a panel framework[10]:

$$R_{i,t} = \alpha_i + \beta\, ROIB_{i,t} + \delta_{BUY} \left(\left| ROIB_{i,t} \right| \times IBUY_{i,t} \right) + \delta_{SELL} \left(\left| ROIB_{i,t} \right| \times ISELL_{i,t} \right) + \varepsilon_{i,t}\,, \qquad (3)$$

where $IBUY_{i,t}$ ($ISELL_{i,t}$) corresponds to the ratio of the net insider purchases (sales) on day t to the total volume of that day for stock i, and $\left| ROIB_{i,t} \right|$ is the relative order imbalance in absolute value. To validate our "efficiency-creating actions by insiders" hypothesis, the coefficient δ_{BUY} (δ_{SELL}) should be positive (negative) and statistically significant for insider purchases (sales). Once controlled for the general relation between the return and the *ROIB*, this result indicates that the *ROIB* observed on insider purchase (sale) days impacts marginally more on the return than on other days, and this is attributed to differential incorporation of information into price occasioned by insider purchases (sales). Such a result is only compatible with information incorporation into prices on insider trading days. Moreover, the use of a fixed-effect panel regression approach allows us to control for omitted variables (e.g., firm characteristics) that are constant through time.

To conclude this section, we want to stress that the biases potentially affecting the abnormal return as a proxy of information incorporation into price (the causation problem and the strategic behavior of informed investors) are less likely to affect our approach. This is because our measure captures something that is specific to the functioning of the market, which is the speed of convergence to market efficiency. This dimension is less subject to manipulation/strategic actions by insiders. What we really want to do is to assess empirically whether insiders bring new and useful information into asset prices with their trading activities, controlling as much as possible for other impacts.

2. Data Sources and Summary Statistics

2.1. Trade, quote and imbalance data

Trade and quote data come from the NYSE's TAQ database. Our sample period ranges from January 1995 until the end of September 1999. The TAQ database includes intraday transactions data for all securities listed on the NYSE, AMEX and the NASDAQ stock exchange. We dropped NASDAQ stocks from our sample because it is difficult to sign these trades (see Christie and Schultz, 1999). Intraday

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[10] We owe special thanks to Richard Roll for having suggested this specification.

data are known to be prone to a number of anomalous records. Therefore, we use the same rules as in Chordia *et al.* (2002) to filter out the data. We excluded trades:

- with no price information, a negative price or a price superior to $999;
- with no quantity;
- recorded before or after the closing time.[11]

For the quotes, we deleted records:

- with negative bid-ask spread;
- with negative quoted depth;
- established before or after the closing time.

At this stage, from an initial sample of 329,705,317 quotes and 208,732,464 trades, we obtain 329,687,111 and 208,472,712 filtered quotes and trades, respectively.

The next step is the determination of the number of buys and sells for each day and each stock, which are essential to compute the imbalance data. We use the Lee and Ready (1991) algorithm to infer trade direction. This algorithm classifies a particular trade as buyer- (seller-) initiated if its price is larger (smaller) than the prevailing mid-quote (average between the ask and the bid prices), and a trade at the mid-quote is classified as a buyer- (seller-) initiated if the last price change prior to the trade is positive (negative).

2.2. Legal insider trading data

[11] The last trade is assumed to occur no later than 4:05 pm since transactions are commonly reported up to five minutes after the official close, 4:00 pm.

We used the Securities and Exchange Commission (SEC) Ownership Reporting System (ORS) data files to extract corporate insider purchases and sales. These data comes from First Call/Thomson Financial Insider Research Services Historical Files. The ORS systems contain records of security transactions by people with beneficial ownership of securities, primarily officers, directors and principal stockholders of a corporation. We kept only SEC Form 4 data from the ORS database, which corresponds to the statement of changes in beneficial ownership of securities. For intraday stock data availability reasons, the sample period studied spans from January 1995 to the end of September 1999. We kept only open market and private transactions and we excluded the ones with less than 100 shares to focus only on the more meaningful events. Therefore, the initial sample encompasses 113,506 insider transactions over the period examined. Following Lakonishok and Lee (2001), we applied filter rules to eliminate the following records: duplicated, amended, with no price information, with a recorded date preceding the transaction date, with a recorded date occurring 31 days (or more) after the due date. As a last filter, we cross-checked the ORS price and volume information against that reported by the TAQ database. Therefore, we dropped from the sample records with a price not within the range of prices of that day, and with a volume exceeding the number of shares exchanged on that day. The application of these filters results in a sample of 109,847 insider trades.

To define our event days (days for which we have an insider purchase or an insider sale) we use the same methodology as in Fidrmuc *et al.* (2006), which consists of taking the net transaction for days for which we have more than one transaction (e.g., a purchase of 300 shares and a sale of 150 shares on a given day become a net purchase of 150 shares for that day, and a purchase of 300 shares and a sale of 400 shares become a net sale of 100 shares). Following this adjustment, our sample covers

59,244 daily aggregated insider trades in 2,110 firms. The number of insider purchase and sale days is 20,023 and 39,221 respectively.

Figure 2 shows the evolution per month of the average proportion of the aggregated insider net purchases and net sales. The proportion of insider purchases (sales) for a given month is computed with respect to the total insider purchases (sales) of the corresponding year. Panel A considers the number of insider trades and Panel B the volume in dollar. These two panels put forward some seasonality pattern. Insider trades (both purchases and sales) seem to be more concentrated at the end of the year. Moreover, insider purchases and their sales seem to share a common seasonality.

2.3. Summary statistics, abnormal returns and market conditions

Summary statistics. Table 1 reports summary statistics of insider trading activities for all NYSE/AMEX common shares between January 1995 and September 1999. Panel A focuses on insider net purchases. The average number of insider net purchase days is 9 per company. The average company subject to an insider purchase has a market value of circa USD 2.6 billion. The average number of shares purchased is 14,612 shares per event, the median being 2,270 shares. In dollar value, the average net purchase transaction amounts to USD 298,350, the size of the median transaction being USD 44,820. Similarly, we report in Panel B the same statistics for the insider net sales. The trading volume is more important for the sale. Insiders seem to be more seller than buyer, and insider sale activities tend to be concentrated on larger firms compared to insider buy activities. This confirms with the results provided by Jenter (2005).

In order to analyze the relative size of the insider transactions, we have computed two ratios: the first one is the ratio of the net insider purchase to the volume of the corresponding day (*Percent Volume*), and the second one is the ratio of the net insider purchase to the market capitalization of the corresponding day (*Percent Mkt Cap*). The average insider net purchase accounts for 12.35 percent of the daily transacted volume, and the median for 3.60 percent. Relative to market capitalization, the ratio ranges from 0 percent to 3.12 percent. In terms of relative size, insider sales and purchases are comparable.

With respect to the trades reporting time to the SEC by the insiders, Table 1 shows two important statistics. These are the disclosure and resting times. The disclosure time is the time difference in number of days between the time at which the transaction is reported to the SEC and the trading time. The average reporting delay is 22.11 and 22.75 days in our sample for the purchases and the sales, respectively. Table 1 shows also the resting time, which is the time in terms of number of days between the theoretical due date and the recorded time. The median of the resting time is 1 day, and the first quartile is 0, both for purchases and sales. Thus, 25 percent of the insider trades were reported with a delay of maximum 30 days. Seventy-five percent of our sample insiders tend to report before the due date.

Market reactions. In this part, we replicate Lakonishok and Lee (2001) event study results to check whether we are in the same empirical context. Table 2 displays the market reaction to insider net purchases and sales around the transaction dates. We compute the daily abnormal returns using a Beta-one model, which consists of subtracting the daily market portfolio return from the daily return of each company. We use the daily equally weighted CRSP index as a proxy for the market portfolio.

We calculate both two-day ($CAR_{0,1}$) and five-day ($CAR_{0,4}$) average cumulative abnormal returns by taking the average of the abnormal returns for each insider transaction.

For the entire sample, the two-day (five-day) abnormal returns are 0.144 (0.417) and 0.278 (0.225) percent for net purchases and net sales, respectively. The two-day average CAR for the purchases is lower than the one for the sales. However, once we increase the length of the event window, the average CAR on insider net sale days is smaller compared to the average CAR on insider net buy days. We have also provided the average CAR as a function of the trade size. As expected, the market impact appears to increase with trade size. Although these abnormal returns are statistically significant at conventional levels, they represent a weak response economically to insider trades, results consistent with the ones reported by Lakonishok and Lee (2001).

It is quite puzzling to observe also positive abnormal returns for insider sales. We see at least four possible explanations for this result: (1) in comparison to buys, insider sells are more likely to be driven by other motives (e.g., such as diversification and liquidity reasons) than private information (e.g., Lakonishok and Lee, 2001; Jeng *et al.*, 2003; Fidrmuc *et al.*, 2006); (2) this result suggests also that insiders seem to sell stock when the market is dominated by the buy side, probably due to a positive public announcements. Indeed, Huddart *et al.* (forthcoming *Journal of Accounting and Economics*) document that insiders sell after good news earnings announcements. The last two potential explanations have already been mentioned in the introduction: (3) insiders have some market timing ability (Jenter, 2005; Piotroski and Roulstone, 2005); (4) the CAR is not a good proxy to capture information asymmetry.

Market conditions. Table 3 displays simple and intuitive measures to compare market conditions between days of insider trades (IT) and the other days (NoIT), using both intraday transaction and quote data. The variables are first measured for each stock and for each day. Once we have our daily observations, we compute the percentage difference using the following procedure. We compute the average of the considered variable over IT-day ($\overline{X}_i^{IT}$) and NoIT-day ($\overline{X}_i^{NoIT}$). We then take their difference, and divide it by the average on NoIT-day. This gives us a percentage abnormal change in price due to insider trading for each of our sample stock over the studied period. To get the average percentage difference (*'percentage-difference'*), we average it across our sample stocks according to the following equation:

$$percentage-difference=\frac{1}{N}\sum_{i=1}^{N}\frac{\overline{X}_i^{IT}-\overline{X}_i^{NoIT}}{\overline{X}_i^{NoIT}}, \qquad (4)$$

where N denotes the number of firms in the sample. Table 3 provides also the '*p-value'* to check whether the *'percentage-difference'* is statistically different from 0. The variables (X_i) are either daily average (e.g., *'price'*, *'percentage quoted spread'*) or daily accumulation (e.g., *'trade volume'*, *'quantity volume'*).

Though having significant positive abnormal returns, the price is on average lower on insider net purchase days and higher on insider net sale days, in comparison to other days. With respect to volume, insider purchase days are days with higher volume, both in terms of trade and share exchanged. However, on insider net sale days the trade and quantity volume is lower, and not statistically different from the other days in dollar value. These results are consistent with the recent findings provided by Jenter (2005) and Piotroski and Roulstone (2005) suggesting insiders' market timing ability.

The percentage quoted spread widens on insider purchase days. This contrasts to some extent with the results provided by Chung and Charoenwong (1998). According to their analysis, market makers establish larger spreads for stocks with a greater extent of insider trading, but they find no evidence of spread changes on insider trading days. The percentage quoted spread narrows on insider sale days. Combined with the result reported in the previous sub-section on the CAR, the contraction of the spread on insider sale days could suggest the reduction of the information asymmetry on the market, likely due to public announcements. In fact, Huddart *et al.* (forthcoming *Journal of Accounting and Economics*) document that insider trades tend to cluster on days after earning announcements, and Chae (2006) shows that volume is higher and measures of information asymmetry are lower after earning announcements.

The impact of insider trades on market depth goes in the opposite direction. Our depth measures are greater on insider purchase days and lower on insider sale days. To gain a better understanding of the impact of insider trading on market liquidity, we used the *'composite liquidity'* measure proposed by Chordia *et al.* (2001), which corresponds to the ratio between the *'percentage quoted spread'* and the *'dollar depth'*. This measure suggests a negative impact of insider net purchases and a positive impact of insider net sales on market liquidity. For the purchase days, the increase in the spread is not compensated by an increase in the depth, and for the sales, a decrease in the spread is not vanished by a decrease in the depth. Consequently, insider purchase days are days with low liquidity, and insider sale days are days with high liquidity. Insiders on the buy side consume market liquidity. In exchange for absorbing liquidity on the market with their purchases, do insiders contribute to market efficiency by hastening price discovery? On the sell side, our result suggests that insiders provide market liquidity, which is in itself a contribution to the efficiency of the financial system.

Table 3 compares also trade imbalance measures on days involving insider trades with that on the other days. It is important to note that, both for the insider purchase days and sale days, the *ROIB* and the *volume ROIB* are not statistically different from the other days.[12] Based on these two measures, insider trades do not modify on average the trade imbalance, but what about the sensitivity of the return to the trade imbalance? This question is explored in the next section.

3. Results

3.1. Are insider trades informative?

The analysis of the abnormal returns in the previous section showed that financial markets offer a week response to insider purchases, and the response has not the expected sign for insider sales. Moreover, insiders do not modify significantly the trade imbalance with their transactions. Now, we turn to the analysis of the sensitivity of the return to the order imbalance on insider purchase and sale days using Equation (3). Remember that if we expect insider trades to convey valuable information about future prices, we must observe increasing price sensitivity on insider trading days. According to Equation (3), this corresponds to a significant positive (negative) δ_{BUY} (δ_{SELL}). Table 4 shows the fixed effect panel regression estimation of this equation. The dependent variable is the daily return over time.

[12] The results given by the value *ROIB* is quite puzzling but seems to be driven by some extreme values.

Price sensitivity change due to insider trades. Model 1 provides an analysis of the price sensitivity change induced by insider trades. The independent variables are the signed relative order imbalance (*ROIB*), the cross product between the absolute *ROIB* and the ratio of insider net purchases on a given day to the total volume of that day ('*insider buy*'), and the cross product between the absolute *ROIB* and the ratio of insider net sales on a given day to the total volume of that day ('*insider sell*'). The coefficients of these two cross-product variables measure the abnormal price sensitivity change induced by insider purchases and sales, respectively. They correspond to the coefficients δ_{BUY} and δ_{SELL} of Equation 3. The coefficient of *ROIB* is 0.02410 and statistically significant, which shows that a positive imbalance (number of buys > number of sells) impacts positively the return. The coefficient of '$|ROIB|$ x *insider buy*' is also positive and statistically significant. This indicates that the sensitivity of the return to trade imbalance on insider purchase days is higher than the sensitivity in other days, which is a clear indication of information incorporation into prices. The coefficient of '$|ROIB|$ x *Insider Sell*' is not significant, and does not have the expected sign. This result suggests that insider sales are either not information-based on average or the investors (and/or the market makers) are not able to figure out their presence in the market.

Price sensitivity change due to insider abnormal trades. Since their physical and human capital is invested disproportionately in their company (e.g., Hall and Murphy, 2002; Becker, 2006), insiders are known to be structurally more sellers than buyers of their own company stocks, mainly for diversification and liquidity reason (e.g., Lakonishok and Lee, 2001, Iqbal and Shetty, 2002; Jenter, 2005). In order to isolate the effect of information-based insider trading on price sensitivity we need to control for managers' incentives to diversify. To estimate the normal level of insider trading, we regress the percentage of insider net purchases (and net sales) on a set of determinants (as in Jenter (2005)), and the insider abnormal purchases (sales) correspond to the unexplained part of the regression. The considered determinants for the regressions are such as follows: *total return over the last 12 months* (corporate insiders are more likely to rebalance their portfolios after large price changes), *market capitalization* (insiders in large firms are more likely to sell company shares than insiders in small firms), *total stock return volatility over the last 12 months* (Meulbroek (2000) shows that managers in more risky companies tend to sell equity more aggressively). We control also for changing firm risk using the volatility change between two successive 6-month periods previous to the considered insider trade. These first step regressions (for both purchases and sales) have significant Fisher statistics, with all the estimated coefficients statistically significant.[13]

The estimation of Equation 3 using insider abnormal trades is given in the column corresponding to Model 2 in Table 4. In order to have robust standard errors, the regressions have been estimated using GMM estimator. Once we control for trades likely realized for diversification reason, both insider purchases and sales are hastening significantly price discovery. The coefficient of '$|ROIB|$ x *insider abnormal sell*' is -0.02361. It has the expected negative sign and is statistically significant suggesting that the returns on insider sale days are more sensitive to order imbalance of other traders. If the imbalance is negative on insider sale days, their trading amplifies the impounding of the order imbalance into the (negative) returns. If the imbalance is positive, insider sale trades attenuate the buy order imbalances of

[13] For the ease of the exposition, these first step regressions are not displayed in Table 4.

others. This is a clear indication that insiders allow information incorporation into prices by their abnormal selling activities.

Model 3 and Model 4 extend the specification of Model 2 by controlling also for market conditions on insider trading days. Indeed, according to Table 3, insider trading days have market conditions in terms of volume or liquidity different from ‘other’ days. Ignoring these aspects in the specification could lead to the conclusion of increasing price sensitivity while it could be a consequence of a difference in terms of liquidity for example. Model 3 shows that once we control for the volume of the trading day (in percentage of the total number of shares outstanding), and the liquidity (measured as in Table 3 by the ratio between the *‘percentage quoted spread’* and the *‘dollar depth’*), the coefficients of interest remain significant. Our results seem not to be driven by market conditions prevailing on insider trading days. Note that the control variables in Model 3 and Model 4 have the expected sign with respected to the liquidity measures. The lower is the market liquidity, the higher the sensitivity of the return to the order imbalance, and the higher (lower) is the spread (depth), the higher is the sensitivity of the return to the order imbalance.

Overall, our results suggest that insider (abnormal) trading allows faster price discovery.

Price sensitivity on reporting days. Table 5 shows the analysis on the reporting days. The official reporting day does not always correspond to the day on which the reporting is made public. There is a time delay of a few days, which varies from case to case (Chang and Suk, 1998). This is the reason why we have also analyzed the days subsequent to the reporting day. We estimate the same panel regression model. Besides of identifying days of insider trading, we have also identified days of reporting. The variable *'Reporting0_buy'* (*'Reporting0_sell'*) takes the value of the aggregated insider net purchases (sales) expressed in percentage of the daily trading volume on the reporting day and 0 otherwise. The following three subsequent days to the reporting day are identified by *'Reporting1'*, *'Reporting2'* and *'Reporting3'*, respectively.

The results provided in Table 5 suggest that information is significantly incorporated into prices on the reporting day of an aggregated insider net purchase. The coefficient associated with the cross product variable '$\left|ROIB\right| x$ *Reporting0_buy*' is positive (0.00084) and statistically significant. This result underlines the importance of the reporting imposed by regulation, because this activity also allows additional information to be incorporated into asset prices. The change in the return sensitivity to an order imbalance due to the reporting of insider purchases is also significant two days after the recording days and even much stronger. For the reporting of aggregated net insider sales, additional information seems to be impounded the day after the reporting.

3.2. Robustness checks

This sub-section is devoted to some robustness analyses. First, we want to be sure that our result is not due to chance. Then, we consider the insider trades in dollar. We also perform the same empirical analysis using two alternative measurements of *ROIB*. Furthermore, we remove from our insider events, days for which the insider abnormal purchases (sales) are lower than the first decile, and greater than the ninth decile.

Are our results due to chance? We implement a model-based bootstrap (MbM) scheme to test whether our result is due to chance (see Davison and Hinkley, 1997). The used bootstrap scheme is as follows:

1. We first estimate Equation (3) without taking into account the cross product variable between the *ROIB* and insider net abnormal purchases and sales: $R_{i,t} = \alpha_i + \beta\, ROIB_{i,t} + \varepsilon_{i,t}$;
2. We then compute for each stock the residual of the estimated model ($e_{i,t}$) such as $\hat{e}_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}\, ROIB_{i,t})$;
3. For each stock, we randomly draw a residual from the corresponding previous series, and then we recompose the initial return series by adding the drawn residual ($\hat{e}^*_{i,t}$) to the estimated return: $\hat{R}^*_{i,t} = (\hat{\alpha}_i + \hat{\beta}\, ROIB_{i,t}) + \hat{e}^*_{i,t}$;
4. With our new return series we re-estimate the model presented in Equation (3).
5. We save the heteroscedastic consistent t-statistic;
6. Step 3 to 5 is repeated 1,000 times.

In this way, we get a simulated distribution for the t-statistics under the null hypothesis of non-contribution of insider trading to market efficiency. If our result is not due to chance, we expect the t-statistics of the coefficients δ_{BUY} and δ_{SELL} to be greater than those obtained through the MbB simulations at conventional levels. Table 6 Panel A gives the number of times the simulated t-statistics is superior to our original t-statistics. We provide also the number of times the simulated p-value is lesser or equal to 0.05. These results clearly show the robustness of our finding according to which insider abnormal purchase and sale days permit faster price discovery.

Insider trades in dollar. Panel B displays the estimation of Model 2 in Table 4 using insider abnormal dollar trades instead of number of shares. The use of the dollar volume does not modify the results presented in Table 4.

Trade ROIB versus volume and dollar ROIB. We have replicated Model 2 of Table 4 using alternative measures for *ROIB*. Table 6 Panel C provides the estimation of Equation (3) using the *quantity ROIB* and the *dollar ROIB*. We get almost the same result.

Censoring insider trades. To check whether our results are not driven by insider larger trades, we remove from the insider episodes, days for which the insider abnormal purchases (sales) are lower than the first decile, and greater than the ninth decile. The change in the return sensitivity to order imbalance due to purchases (sales) remains significant and with the expected sign, suggesting that it is not a small sub-set of large trades that contain private information.

4. Conclusion

So far, empirical evidence supporting the contribution of insiders to information efficiency is limited. Works relying on short-term abnormal returns are at best ambiguous, being potentially hampered by endogeneity problem and insiders' strategic behavior, and show only limited impacts. The long-term abnormal performance of insiders' portfolios may simply be due to the public release of information in the months following insider trades.

The contribution of this paper stems from the methodology we applied. Using insights from the recent microstructure literature, we studied, in a panel data analysis setting, the change in sensitivity of the return to the relative order imbalance induced by insider trading. The modest data requirements of our approach allowed us to deal with a really large sample of 59,244 daily aggregated insider trades in 2,110 firms quoted on either the NYSE or the AMEX during the period 1995-1999.

Our results are unambiguous and robust with respect to several definitions of the relative order imbalance: insiders do significantly contribute to faster price discovery on insider trading days; and disclosure requirements also contribute (but to a lesser extent) to market efficiency. The necessary condition for allowing regulated insider trading is fulfilled. Is this contribution sufficient given the price paid by uninformed agents? This is an open ethical question.

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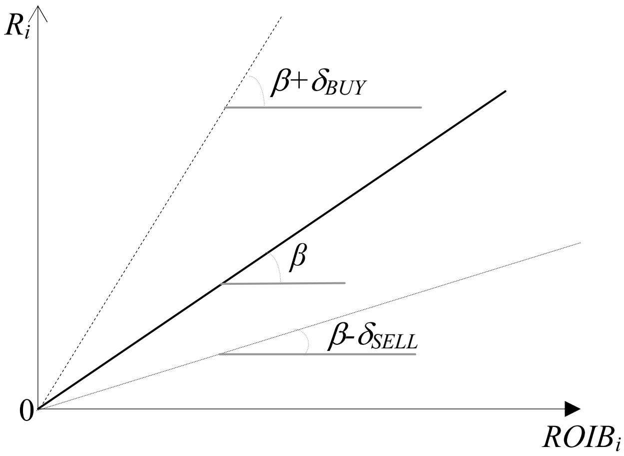
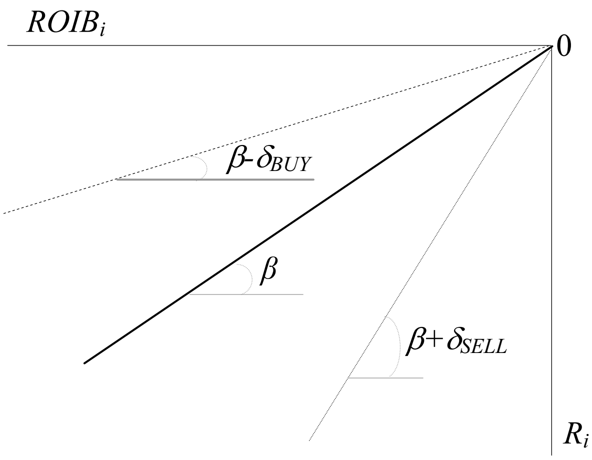
Figure 1. Abnormal price sensitivity to relative order imbalance

This figure displays the expected abnormal price sensitivity to relative order imbalance due to insider trading. The X-axis and Y-axis represent the relative order imbalance (*ROIB*) and the return (*R*) for stock *i*, respectively. Panel A (Panel B) depicts the case where a positive (negative) return is associated with a positive (negative) *ROIB*. The coefficient β measures the normal level of the price sensitivity to the *ROIB*. The coefficients δ_{BUY} and δ_{SELL} capture the abnormal change in the sensitivity induced by insider buy and sell transactions, respectively.



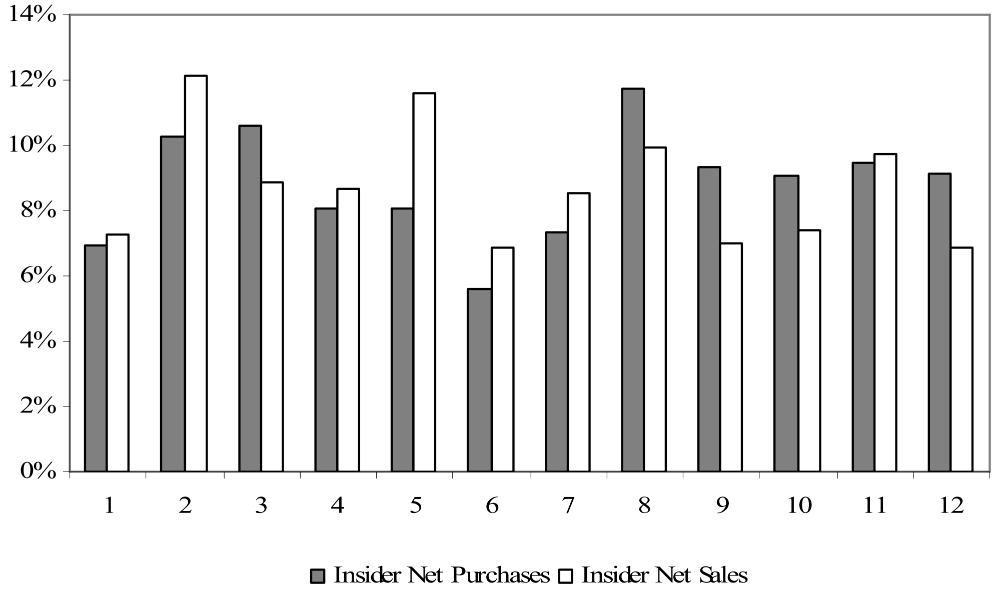
Panel A. R>0 and ROIB>O



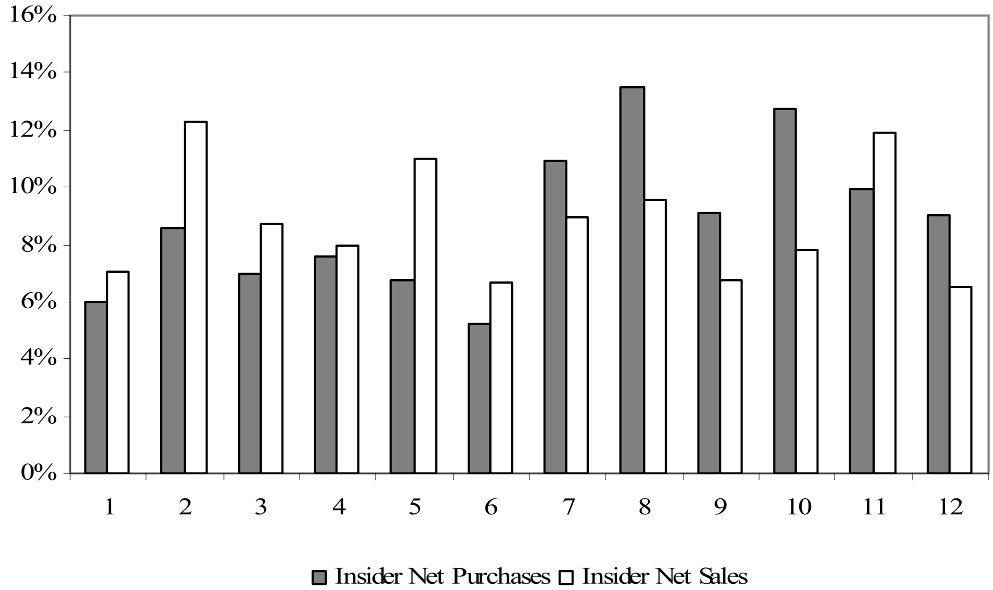
Panel B. R<0 and ROIB<0

Figure 2. Insider trades aggregated per month

This figure displays the evolution of the average proportion of the aggregated insider net purchases and net sales per month. The X-axis represents the month of the year. Panel A and Panel B consider the number of insider trades and the volume in dollar, respectively.



Panel A. Number of trades



Panel B. Volume in dollar

Table 1. Summary statistics of insider trading activities

This table reports summary statistics of insider net purchases (Panel A) and net sales (Panel B) for all NYSE/AMEX common shares over the period from January 1995 to the end of September 1999. The total number of firms in our sample is 2,110. '*Events by firm*' corresponds to the number of insider trade days (net purchase or net sell days) for a sample firm. '*Mkt Cap*' is the market capitalization on the month of the insider trade (number of shares outstanding multiplied by the share price of the corresponding month). The descriptive statistics have been computed with respect to the considered events. '*Trade quantity*' refers to the size in number of shares of the insider net purchases (sales) per event. '*Trade value*' is the net insider purchases (sales) in USD. '*Percentage Volume*' is the ratio of the net insider purchases (sales) to the volume of the corresponding day. '*Percentage Mkt Cap*' is the ratio of the net insider purchases (sales) to the market capitalization of the corresponding month. '*Disclosure time*' is the time (in number of days) between the recorded time and the transaction time. '*Resting time*' is the time (in number of days) between the theoretical due date and the recorded time. Q1 and Q3 correspond to the first and third quartile, respectively.

	Mean	**Min**	**Q1**	**Median**	**Q3**	**Max**
Panel A. Insider net purchases						
Events by firm	9	0	2	6	12	286
Mkt Cap ($'000)	2,632,963	11,337	289,311	606,308	1,670,704	209,144,834
Trade quantity	14,612	100	1,000	2,270	10,000	5,799,432
Trade value ($)	298,350	200	15,000	44,820	155,000	50,446,608
Percentage Volume (%)	12.35	0.00	0.70	3.60	15.49	99.43
Percentage Mkt Cap (%)	0.03	0.00	0.00	0.01	0.03	3.12
Disclosure time	22.11	0.00	14.00	21.00	30.00	70.00
Resting time	2.47	-30.00	0.00	1.00	4.00	38.71
Panel B. Insider net sales						
Events by firm	19	0	2	9	26	233
Market Value ($'000)	7,217,954	11,337	526,281	1,591,086	6,032,857	209,144,834
Trade quantity	25,561	100	2,500	7,400	20,000	6,610,129
Trade value ($)	1,031,844	114	74,380	237,420	753,800	243,529,545
Percentage Volume (%)	11.91	0.00	1.34	4.88	15.05	99.80
Percentage Mkt Cap (%)	0.05	0.00	0.00	0.01	0.04	19.16
Disclosure time	22.75	0.00	14.20	22.00	30.00	70.00
Resting time	1.89	-30.00	0.00	1.00	3.00	38.00

Table 2. Market reactions to insider trading activities

This table reports average cumulative abnormal returns in percentage around insider net purchases and insider net sells for all companies in the sample. Panel A deals with the all sample, and Panel B provides a split of the sample by trade size. *Qx* denotes the quartile *x* reported in Table 1, and $CAR_{0,1}$ ($CAR_{0,4}$) corresponds to the average of the cumulated abnormal return between day 0 and day +1 (+4) relative to the transaction date. As in Lakonishok and Lee (2001), we calculate daily abnormal returns by subtracting the equally weighted CRSP index daily return from the daily return of a firm's stock.

	Net purchases		**Net sells**	
	$CAR_{0,1}$	**$CAR_{0,4}$**	**$CAR_{0,1}$**	**$CAR_{0,4}$**
Panel A. All sample				
Abnormal returns	0.144	0.417	0.278	0.225
p-value	*0.000*	*0.000*	*0.000*	*0.000*
Panel B. Split by trade size				
Trade Value <= Q1				
Abnormal returns	0.023	0.187	0.104	0.021
p-value	*0.729*	*0.033*	*0.009*	*0.718*
Q1 < Trade Value <= Q2				
Abnormal returns	0.200	0.522	0.274	0.214
p-value	*0.001*	*0.000*	*0.000*	*0.000*
Q2 < Trade Value <= Q3				
Abnormal returns	0.130	0.524	0.325	0.333
p-value	*0.033*	*0.000*	*0.000*	*0.000*
Q3 < Trade Value				
Abnormal returns	0.225	0.435	0.411	0.331
p-value	*0.000*	*0.000*	*0.000*	*0.000*

Table 3. Comparison of market conditions between days of insider trading and other days

This table compares market conditions between days of insider trading and other days. The considered variable are either daily average (e.g., *'price'*, *'percentage quoted spread'*) or daily accumulation (e.g., *'trade volume'*, *'quantity volume'*). *'%Difference'* corresponds to the difference in percentage between these two categories of days, averaged across stocks. The *'ask'* (*'bid'*) price is the price at which the market maker is willing to sell (buy) the stock. The '*quoted spread*' corresponds to the difference between the ask price and the bid price. The '*midpoint*' is the average of the ask price and the bid price (*(ask+bid)/2*). The *'effective spread'* corresponds to the absolute difference between the transaction price and the midpoint, divided by 2. The '*ask depth*' ('*bid depth*') is the maximum quantity of stock the market maker is willing to sell (buy) at the ask price. The *'dollar depth'* is the weighted sum of the ask depth and the bid depth, the weights being the ask price and the bid price. The reported p-value tests whether the *'%Difference'* is statistically significant or not.

Market variables	**Description**	**Net Purchases**		**Net Sales**	
		%Difference	*p-value*	%Difference	*p-value*
Price	Average transaction price	-7.7	*0.00*	4.0	*0.00*
Trade volume	Number of trades	2.8	*0.00*	-1.4	*0.00*
Quantity volume	Number of shares exchanged	5.5	*0.00*	-2.8	*0.00*
$ volume	Number of shares exchanged in dollar value	-2.5	*0.00*	1.3	*0.01*
Percentage quoted spread	Average of (*quoted spread / midpoint*)	7.0	*0.00*	-3.5	*0.00*
Percentage effective spread	Average of *(effective spread / midpoint)*	1.5	*0.00*	-0.7	*0.00*
Ask depth	Average depth at the *'ask'* side	4.0	*0.00*	-2.0	*0.00*
Bid depth	Average depth at the '*bid*' side	6.4	*0.00*	-3.3	*0.00*
Depth	Average of *'ask depth + bid depth'*	5.2	*0.00*	-2.7	*0.00*
Composite liquidity	Average of *'percentage quoted spread / dollar depth'*	12.8	*0.00*	-6.5	*0.00*
Relative order imbalance	Buys minus sells, divided by buys plus sells (in number)	-84.0	*1.00*	42.9	*0.43*
Volume relative order imbalance	Buys minus sells, divided by buys plus sells (in volume)	86.0	*0.71*	-43.9	*0.80*
Value relative order imbalance	Buys minus sells, divided by buys plus sells (in dollar)	-654.5	*0.05*	334.1	*0.40*

Table 4. Insider trades and price sensitivity change to relative order imbalance

This table provides fixed effect panel regression estimation of Equation (3). For each model, the dependent variable is the daily return. Model 1 provides an analysis of the price sensitivity change induced by insider trades. *ROIB* is the signed order imbalance, $|ROIB|$ is the absolute value of *ROIB*, *'insider buy'* (*'insider sell'*) corresponds to the ratio of the insider net purchases (sells) on a given day to the total volume of that day. To compute the *p-value* we use White's heteroscedasticity-consistent covariance matrix estimators. Model 2 provides an analysis of the price sensitivity change induced by insider abnormal trades. *'insider abnormal buy'* (*'insider abnormal sell'*) corresponds to the unexplained part of a first step regression, where *'insider buy'* (*'insider sell'*) are regressed on a set of determinants. Model 3 and Model 4 extend the specification of Model 2 by controlling for volume and liquidity. The used control variables are '*percentage volume*' (volume of the trading day divided by the total number of shares outstanding), *'composite liquidity'*, *'percentage quoted spread'*, and *'depth'*. In order to have robust standard errors, the regressions have been estimated using GMM estimator. P-values are within brackets. We do not report firm specific fixed effects in the table. *'N'* denotes the number of observations entering into the panel estimation.

Independent variables	Model 1	Model 2	Model 3	Model 4
ROIB	0.02410 (0.00)	0.02410 (0.00)	0.02330 (0.00)	0.02046 (0.00)
$\|ROIB\|$ x *insider buy*	0.01656 (0.00)			
$\|ROIB\|$ x *insider sell*	0.00167 (0.27)			
$\|ROIB\|$ x *insider abnormal buy*		0.01720 (0.00)	0.01672 (0.00)	0.01725 (0.00)
$\|ROIB\|$ x *insider abnormal sell*		-0.02361 (0.00)	-0.02367 (0.00)	-0.02384 (0.00)
ROIB x *percentage volume*			0.01393 (0.25)	
ROIB x *composite liquidity*			6.39934 (0.00)	
ROIB x *percentage quoted spread*				0.37446 (0.00)
ROIB x *depth*				-0.20369 (0.00)
Fisher Test	64422 (0.00)	64,432 (0.00)	40,010 (0.00)	42,179 (0.00)
N	2,042,438	2,042,438	2,042,438	2,042,438
Adjusted R^2	0.086	0.086	0.089	0.093

Table 5. Insider reporting days and price sensitivity change to relative order imbalance
This table provides fixed effect panel regression estimation of Equation (3) where we have also identified insider reporting days (*'Reporting0'*) and the successive days. The variable *'Reporting0_buy'* (*'Reporting0_sell'*) takes the value of the aggregated insider net purchases (sales) expressed in percentage of the daily trading volume on the reporting day and 0 otherwise. The following three subsequent days to the reporting day are identified by *'Reporting1'*, *'Reporting2'* and *'Reporting3'*, respectively. In order to have robust standard errors, the regressions have been estimated using GMM estimator. *N* denotes the number of observations entering into the panel estimation.

Independent variables	Coefficient	P-value
ROIB	0.02410	0.00
$\vert ROIB \vert$ x *insider abnormal buy*	0.01666	0.00
$\vert ROIB \vert$ x *Insider abnormal sell*	-0.02357	0.00
$\vert ROIB \vert$ *x Reporting0_buy*	0.00084	0.03
$\vert ROIB \vert$ *x Reporting1_buy*	0.00021	0.26
$\vert ROIB \vert$ *x Reporting2_buy*	0.00203	0.00
$\vert ROIB \vert$ *x Reporting3_buy*	0.00053	0.22
$\vert ROIB \vert$ *x Reporting0_sell*	0.00008	0.85
$\vert ROIB \vert$ *x Reporting1_sell*	-0.00096	0.05
$\vert ROIB \vert$ *x Reporting2_sell*	-0.00038	0.40
$\vert ROIB \vert$ *x Reporting3_sell*	-0.00025	0.63
Fisher Test	17,573	0.00
N	2,042,438	
Adjusted R^2	0.086	

Table 6. Robustness checks

Panel A shows the results obtained through a model-based bootstrap (MbB) approach to check whether our result is not due to chance. T_{BUY} corresponds to the t-statistic of the coefficient δ_{BUY} in Equation 3. T_{MbB} corresponds to the t-statistic of the same coefficient obtained through the MbB procedure, at each iteration. Panel B displays the estimation of Model 2 in Table 4 using insider abnormal dollar trades instead of number of shares. Panel C replicates also Model 2 in Table 4 using volume *ROIB* and dollar *ROIB*, instead of trade *ROIB*. Panel D considers only insider abnormal trades within the first and last decile.

Panel A. Are our results due to chance?

	Count	Proportion
Abnormal insider purchase		
$T_{MbB} > T_{BUY}$	0	0.00%
p-value$_{MbB}$ < 0.05	48	4.80%
Abnormal insider sell		
$T_{MbB} > T_{BUY}$	0	0.00%
p-value$_{MbB}$ < 0.05	59	5,91%
Number of simulation	1,000	

Panel B. Insider trades in dollar

Independent variables	Coefficient	P-value
ROIB	0.02410	0.00
$\lvert ROIB \rvert$ x *$ insider abnormal buy*	0.01511	0.00
$\lvert ROIB \rvert$ x *$ insider abnormal sell*	-0.02506	0.00
Fisher Test	64,433	0.00
N	2,042,438	
Adjusted R^2	0.086	

Panel C. Volume and dollar ROIB

	Volume ROIB		Dollar ROIB	
Independent variables	Coef.	P-value	Coef.	P-value
ROIB	0.01864	0.00	0.01864	0.00
$\lvert ROIB \rvert$ x *insider abnormal buy*	0.00864	0.00	0.00860	0.00
$\lvert ROIB \rvert$ x *insider abnormal sell*	-0.01116	0.00	-0.01120	0.00
Fisher Test	74,162	0.00	74,186	0.00
N	2,196,212		2,196,212	
Adjusted R^2	0,098		0.098	

Panel D. Censoring the data

Independent variables	Coefficient	P-value
ROIB	0.02452	0.00
$\lvert ROIB \rvert$ x *insider abnormal buy*	0.02415	0.00
$\lvert ROIB \rvert$ x *insider abnormal sell*	-0.08874	0.00
Fisher Test	61,197	0.00
N	1,899,108	
Adjusted R^2	0.088	